Deep Learning for Model-Free Prediction of Thermal States of Robot Joint Motors

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Abstract: In this work, deep neural networks made up of multiple hidden Long Short-Term Memory (LSTM) and Feed-Forward layers are trained to predict the thermal behavior of the joint motors of robot manipulators. A model-free and scalable approach is adopted. It accommodates complexity and uncertainty challenges stemming from the derivation, identification, and validation of a large number of parameters of an approximation model that is hardly available. To this end, sensed joint torques are collected and processed to foresee the thermal behavior of joint motors. Promising prediction results of the machine learning based capture of the temperature dynamics of joint motors of a redundant robot with seven joints are presented.

Keywords: Robotics, Thermal Management, Artificial Intelligence / Machine Learning.

1. INTRODUCTION

Robots are commonly used to achieve repetitive and hazardous tasks in industry and society. Meanwhile, they increasingly and skillfully assist and augment humans. Included are applications with a pronounced level of physical interactions between humans and robots, such as using a robot as a companion (Basha (2025)), home-helper and caregiver (Tsui et al. (2025),Gkiolnta et al. (2025)), as well as a prosthesis (Kim et al. (2025)). In this respect, high payload manipulations, large joint accelerations, and motions with specific configurations (see, e.g., Fig. 1) can induce an overheating of joint motors of robots. Excessive motor temperatures are detrimental is many ways. They can accelerate the degradation of insulation materials and reduce the motor efficiency (Yehorov et al. (2025)) along with jeopardizing the positioning accuracy of the robot because of axial deformations and drifts (Soga et al. (2024)).

Most robot manufacturers, including Franka, Kinova, and KUKA, offer built-in functions to shut down the robot once a critical temperature threshold is attained. Whereas this functionality is advantageous to preserve the performance and reliability of motors and surrounding electronic components, an undesired shutdown tends to compromise the robot availability for production and assistance purposes. This situation gets exacerbated as the robot is not equipped with mechanical breaks as in Fig. 1. In this case, critical collisions with the environment might occur, endangering human beings or leading to hardware (i.e., robot, workpiece, workcell, etc) damages. Furthermore, thermal burns represent not only a severe safety issue in physical human-robot-interaction but also a hindrance for elevated user experience that is necessary to engage and sustain a symbiosis between humans and robots.

Predicting the thermal behavior of robot joints is therefore an essential step toward the development of countermeasures that help anticipate overheating, preserve the robot
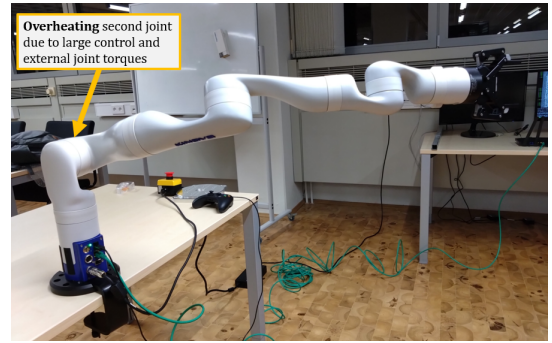

Fig. 1. Robot posture increasing a motor temperature.

availability, prolong its lifetime, and improve its usability. Industry 4.0, industry 5.0, together with society 6.0 are likely to benefit from this capability. In fact, the thermal prediction propels operational efficiency through its significant contribution to the design of thermally uncritical trajectories that preserve the motor performance and thus robot availability in fully automated high-speed low-time-to-market manufacturing. This skill is missing in current industrial applications. Endowing robots with a thermal management based upon machine learning is useful to accommodate uncertainties emanating from *unseen* events. These include the highly dynamic robotized human-centered assistance for smart living and social well-being. These goals requires an approach that turns robot diversity and application uncertainties into competitive advantages in terms of flexibility, transferability, and scalability.

This work predicts the thermal behavior of joint motors. The prediction approach is

- data-driven, paving the ground for an insightful, non-invasive, and inclusive operationalization in real-time.
- model-free through the development of a deep learning-based framework that leverages multiple hybrid layers to capture the unknown dynamics between
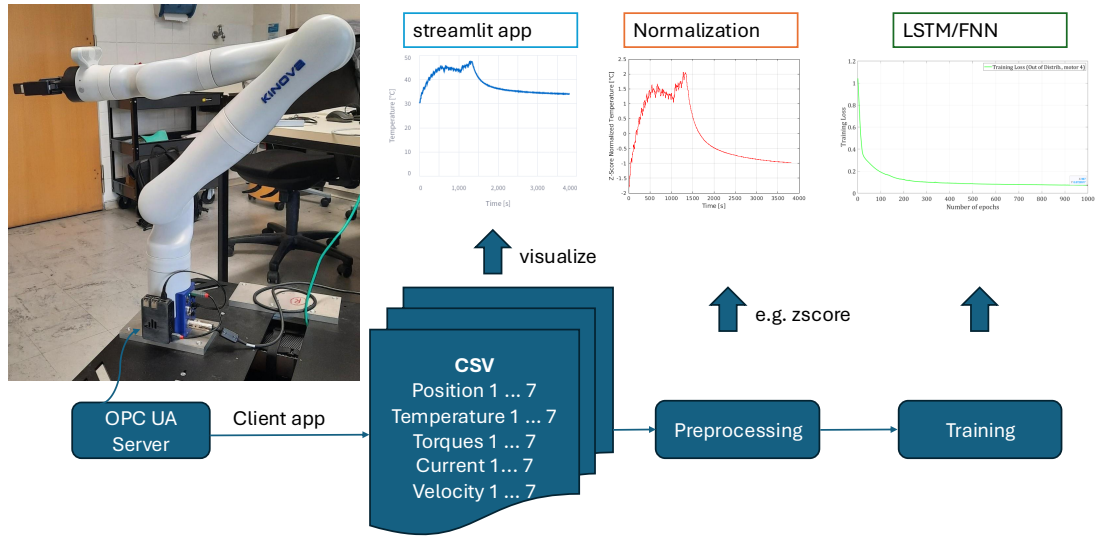
Fig. 2. Kinova data collection via OPC UA Server.

joint actuation and motor temperature. No system-related parametric or actuation profile assumptions are made. Model complexity is thereby avoided. Generalization to new events and transferability to other robot types regardless of the number and type of joint motors are fostered.

- evaluated on data collected from a redundant robot with seven joints (see Fig. 2). Practical advantages of data normalization are highlighted.

2. RELATED WORKS

Predicting the temperature behavior of robot motors has attracted attention in the recent years.

Afaq et al. (2023) focus on thermal management of robotic applications under extreme temperatures. Electronics heating and cooling are considered. A temperature control driven by fuzzy logic is developed and demonstrated to this end. Decreases of extreme high temperature from 50° to 8° are shown. Fan-based forced convection is used to cool electronics. Excessive internal temperatures in a permanent magnet synchronous motor taking non-stationary loads, which might lead to a reduction of its life time, is addressed in Chen et al. (2024). An accelerated degradation model is derived to evaluate the reliability function and predict the lifetime of the PMSM under thermal stress. Geometric backlash and temperature-related drift errors in joints of industrial robots are compensated in Sigron et al. (2023). A model that reflects the thermal expansion of links is developed and used for thermal expansion correction. LSTM Neural Networks (He et al. (2024)) and Pseudo-Siamese Nested LSTM (Cai et al. (2021)) are employed to predict the temperature in Permanent Magnet Synchronous Motors. A trapezoidal torque profile is employed in He et al. (2024) whereas the torque dynamics is not released in (Cai et al. (2021)). A thermal recovery of robot joints is achieved in Jorgensen et al. (2019). To this end, the thermal dynamics is captured as a first order ordinary differential equation subject to constant positive and negative step-like profiles of joint torques. The exponential-based dynamics of the temperature behavior is derived. A parameter identification is carried out to demonstrate the performance of the model for step-like joint torques.

Contributions mentioned thus far are mostly model-driven. They fit with specific robots provided that parameters have been identified in advance. However, parameter identification requires noise robustness and low sensitivity (Zhang et al. (2024), de Hoyos Fernández de Córdova et al. (2024)), which is a time consuming analysis task prone to additional uncertainties due to unseen/unmodeled/truncated dynamics (Shang et al. (2024)). Sometimes, such a process must be repeated from scratch for a given new robot, which inhibits quick and large scale automation involving multiple robots in terms of complexity, workload, and costs. As the robot is hardly accessible, such as in space servicing, identification tasks might be hard to complete because of limited access to pertinent (e.g., excitation) data. Autonomous task completion without human interventions, as expected by Industry 6.0, calls for machine learning-embedded solutions (Carayannis et al. (2024)) that can extend the robot intelligence for self-condition monitoring. The approach proposed in this work also falls into this category. Robot datasets available from standard APIs are harnessed to predict the thermal behavior of its joint motors. Trained machine learning models can be executed by dedicated services of digital twins with which the physical robot is embedded to detect, communicate to other entities, and anticipate detrimental thermal issues. In contrast to related works, no restriction is made on robot types, number of joints, and actuation profiles.

3. METHOD

3.1 System overview

The data from a Kinova Gen3 7 degrees-of-freedom ultra-lightweight robotic arm [kinova], has been recorded using

a specially developed OPC Unified Architecture server (Girke et al. (2024)). Positions, temperatures, torques, velocities and currents of each of the seven joints are stored, via a client application, as parameters in CSV files and subsequently processed for the neural network trainings, see Fig. 2. To cover a wide range of robotic movements, both randomly generated joint angle trajectories and predefined Cartesian trajectories for pick and place tasks, for example, were generated using the Kortex API (Robotics (2025)). The trajectories were initially performed at varying speeds and with different payloads. The recording duration of each set of trajectories was also varied in order to analyze the temperature rise and the cooling behaviour of the joints. For cooling, the robot was positioned in a vertical position, as this joint configuration imposes minimal load on the joints. However, the vertical position was not always used for cooling. To simulate real conditions, movements without intentional cooling were also conducted sequentially. To prevent collisions due to randomly generated joint angles, the random angular values were constrained within minimum and maximum limits. The result of this experiment indicate that joint 2 and joint 4 experience the most temperature increase and cooling. The data is freely available on our streamlit web app, which automatically visualizes the CSV files and displays the specific joint data. [1]

3.2 Temperature profile approximation

The temperature profile can be represented approximately with the Gaussian model (i.e. Gauss2) as shown in Fig. 3 and (1):

$$f(x) = a_1 \cdot \exp\left(-\left(\frac{x - b_1}{c_1}\right)^2\right)$$
$$+ a_2 \cdot \exp\left(-\left(\frac{x - b_2}{c_2}\right)^2\right) \tag{1}$$

With the coefficients and metrics for Fig. 3:
$$a_1 = 34.07, \quad b_1 = 276$$
$$c_1 = 743.2, \quad a_2 = 1.668$$
$$b_2 = -26.71, \quad c_2 = 103$$

Root Mean Squared Error (RMSE): 0.081294
R^2 (coefficient of determination): 0.9897

Although the approximation provides a good result, it has some limitations. The coefficients vary for each temperature profile and must be recalculated. Neuronal networks offer a more generalizable and robust approach to this end.

3.3 Feedforward and LSTM neural networks

Feedforward networks have simplistic strcuture and are limited in their ability to incorporate past values. Recurrent neural networks (RNN) therefore have feedback loops to store past values via hidden states. This allows them to understand long-term dependencies, which results in more stable predictions. However, RNNs lose old information over time. With LSTMs, long-term information is
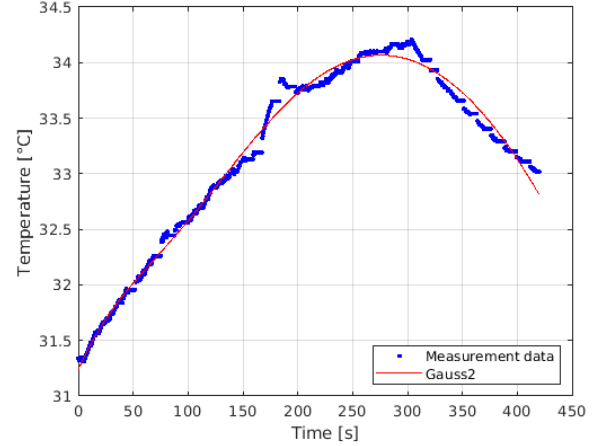
Fig. 3. Approximation of the temperature profile of the 4th joint with the Gauss2 function.

stored more effectively. They feature cell state for long-term memory and hidden state for short-term memory. In addition, the storage and removal of information is controlled via four gates (Input Gate, Forget Gate, Cell Gate, Output Gate). They are therefore used for predictions where past states have an influence on future states (Ljung et al. (2020)).

Table 1 compares the neural network architectures leveraged in this paper.

- FNNs disregard historical information and consider each input independently. While LSTM networks are able to store the context of previous points in time (sequential data) through memory cells and use this information for future predictions (Liu et al. (2019)).
- The structure of FNNs is simple and can be trained with lower computational power and in a shorter time compared to LSTMs, which consists of more complex structures (sates and gates). LSTMs store and update past information.
- Joint temperatures change due to continous load, movement and position. This can be detected by LSTMs, since they were specifically desinged for time series. FNNs are more suitable for regression problems on static data points, similar to the approximation of the temperature profile (see Fig. 3)

We implement and train a deep neural network that combines LSTM as a feature-extractor for time series dependencies in the input torque data and multiple Feedforward layers to take advantage of the extracted features for the subsequent temperature prediction at the network output.
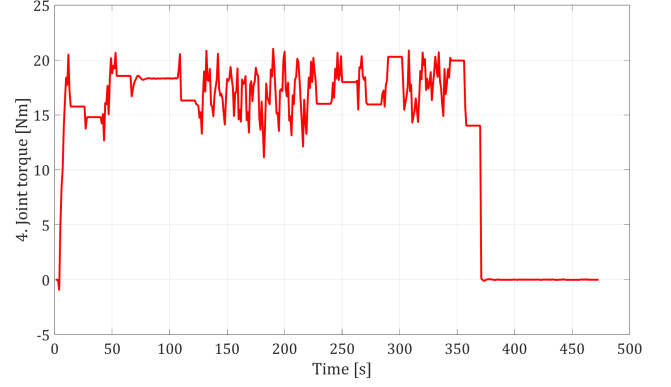
Table 1. Comparison of Feedforward and LSTM neural networks

| Feature	FNN	LSTM
Handles Sequential Data	No	Yes
Computational Complexity	Low	High
Training Time	Fast	Slow
Memory Requirements	Low	High
Suitable for Static Inputs	Yes	No
Suitable for Time-Series Data	No	Yes
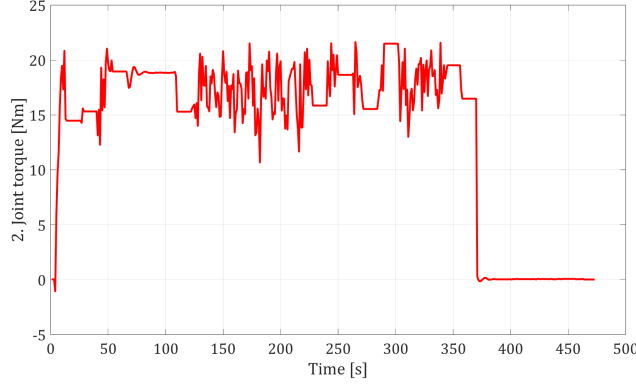
(a) Torque profile of the 2. motor.

(b) Torque profile of the 4. motor.

Fig. 4. Two different non-trivial torque profiles of the robot in Fig. 1. Observe that the profiles go beyond step functions.
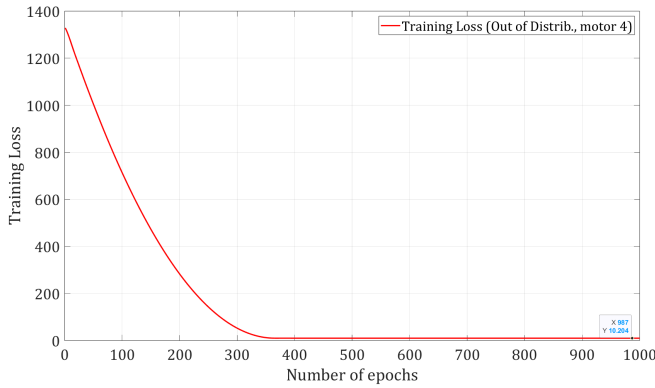
(a) Training loss without data normalization.
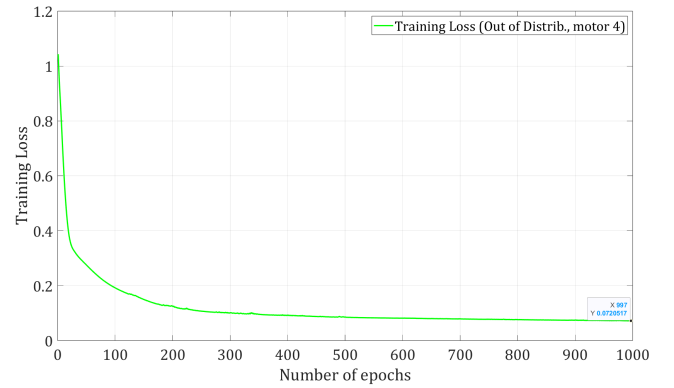
(b) Training loss with z-score data normalization.

Fig. 5. Enhanced convergence velocity and effectiveness of the training loss through data normalization.

4. APPLICATION

Experiments have been carried out to predict the temperature of each of the seven joint motors of the redundant robot in Fig. 1.

4.1 Data acquisition and pre-processing

The collected data allows the utilization of joint positions, torques, velocities, and currents of all seven joints as input features. The selection of the input values for the training can be adjusted as needed, varying from 7 to a total of 28 inputs (Fig. 2). However, the best result was observed with only the joint torques (see Fig. 4) as input features for the neuronal network. The temperature values of the seven joints are used as targets. To evaluate the temperature predictions from the neural networks, randomly selected temperature measurements serve as ground truth.

The setup for collecting joint torques and corresponding motor temperatures is shown in Fig. 2. Recorded profiles of joint torques are rather challenging when compared to step profiles considered in related works. Acquired data are not filtered. A z-score normalization of input (i.e., joint torques) and target (motor temperatures) data is carried out before training. The mean μ and standard deviation σ of temperature data obtained during the normalization are stored. After training, the original temperature data x is reconstructed from the predicted $\tilde{x}$ according

$$x = \tilde{x}\sigma + \mu \tag{2}$$

Data normalization has significantly speed up the training process and enhanced the convergence (see Fig. 5).

4.2 Model training

The mean squared error between network output and target temperature data is adopted as loss function. Back propagation is leveraged for the optimization of network weights. The Adaptive Moment Estimation adapts the learning rate. The probability with which input elements are dropped out (i.e., set to zero) to prevent network overfitting is set to 0.1. A mixture of *tanh*, *elu*, and *sigmoid* are distributed as activation functions (a type per layer) to inject non-linearities into the network. The output layer is equipped with the identity activation function.

4.3 Prediction results

The trained neural network of seven hidden layers (one LSTM layer, six feed forward layers with a decreasing number of neurons toward the output) is fed with torque data. The network input is a dataset *unseen* during training. The goal is to assess the generalization capability of the network when facing new dynamics of the robot. Two generalization tests are completed for each of the seven
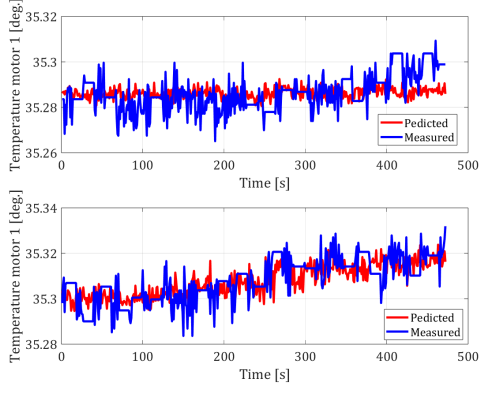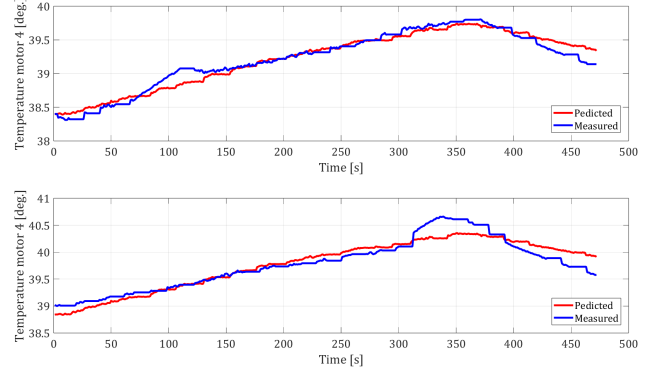
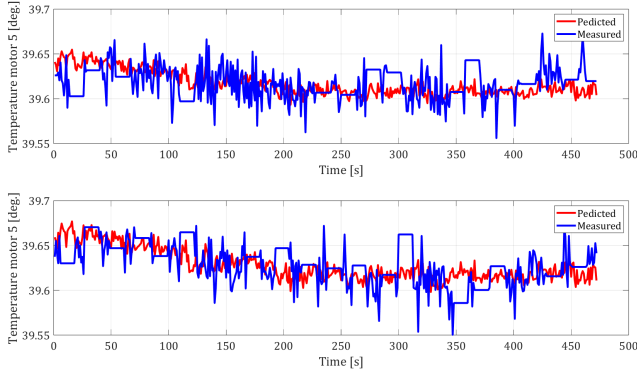(a) Motor 1: Different predictions with **unseen** joint torques.
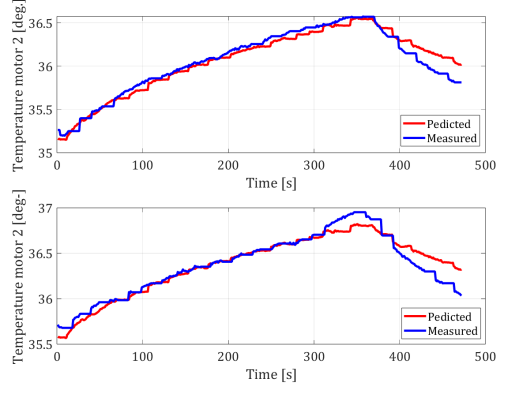
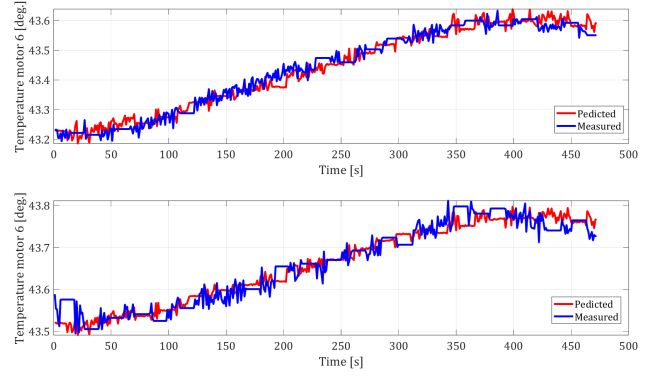(b) Motor 2: Different predictions with **unseen** joint torques.
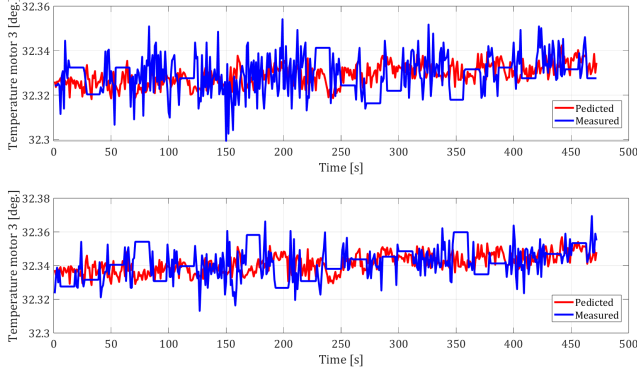
(c) Motor 3: Different predictions with **unseen** joint torques.
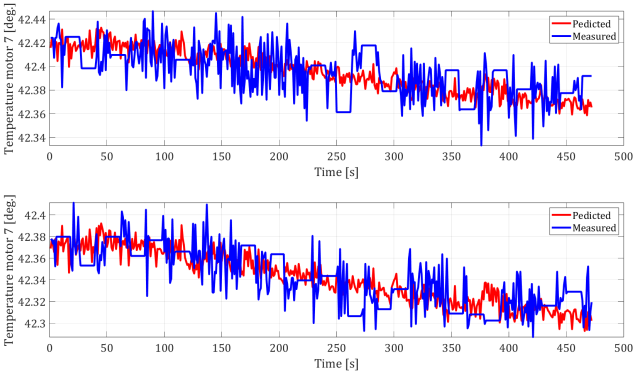
(d) Motor 4: Different predictions with **unseen** joint torques.
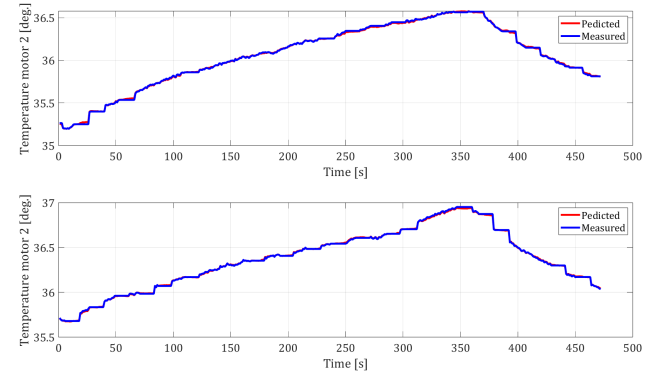
(e) Motor 5: Different predictions with **unseen** joint torques.

(f) Motor 6: Different predictions with **unseen** joint torques.

(g) Motor 7: Different predictions with **unseen** joint torques.

(h) Motor 2: Different predictions with **seen** joint torques.

Fig. 6. Capturing the thermal behavior of joint motors of the robot in Fig. 1 with previously unseen and seen data.

joints. An additional test with seen data is conducted and restricted to the second joint.

Validation and generalization results are shown in Fig. 6. Whereas motor temperatures are predicted with negligible error (below $0.001°$) when the two seen datasets are employed as inputs of the trained network (see Fig. 6.f), the absolute value of the overall prediction error remains below $0.5°$ in the case of totally unseen data (see Fig. 6.a-g). It is worth noting that the small training dataset is randomly generated. The generalization accuracy can be further enhanced by augmenting the amount of training data. Nevertheless, an advantage of working on a small dataset is to assess how a minimum amount of data, energy demand, and a satisfactory accuracy relate. In our specific case, 16 datasets with recording time length as in Fig. 4 is suitable. Insights gained are useful to steer on-board machine learning in mobile robots under energy autonomy constraints.

5. CONCLUSION

This work shows that the temperature behavior of a robot can be predicted in advance without any analytical model about how joint torques map to motor temperatures. The proposed approach is not only model-free but also scales up for any number of joint motors and generalizes when exposed to unseen inputs despite the small amount of training data being used. Its effectiveness is evaluated and demonstrated for complex joint torque profiles and all each of the seven joints of the experimental robot. The proposed framework can help anticipate and alleviate the widespread shutdown of industrial and service robots once a critical temperature is attained, design thermally uncritical joint trajectories, prolong the lifetime of robot motors, and prevent thermal burns in industry and society..

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